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Modeling social coupon redemption decisions of consumers in food industry: A machine learning perspective

Pappu Kalyan Ram [a], Neeraj Pandey [a,*], Jinil Persis [b]

[a] Indian Institute of Management Mumbai, Vihar Lake Road, Powai, Mumbai 400087, India
[b] Indian Institute of Management Kozhikode, Kunnamangalam, Kerala 673570, India

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ABSTRACT

Social couponing is a growing promotional phenomenon in the service industry. However, since the conversion rate of distributed coupons into coupons redeemed for purchase is relatively low, there is a need to understand the redemption decisions of consumers. Lower conversion rates lead businesses to lose both customers and profits. Previous studies have typically focused on social couponing from a business perspective, without exploring factors from the customer's end. The current study explores the factors influencing customers' decision to redeem coupons and highlights the interrelationships between the factors. Data were collected from 353 online customers on their redemption experiences during their food purchases. Structural equation modeling was performed to examine the significance of the factors and establish the predictability of customers' redemption decisions. We then explored different machine learners to identify the best-fitting models for customers' redemption decisions. Results showed that the prediction accuracy of the decision-tree-based models was the highest. These models delineate the role of influencers in various redemption aspects and validate the mediation effects of perceived risk, deal proneness, referral, and consumption frequency. The study also highlights future research areas in the social couponing domain.

1. Introduction

Most consumers have shifted from physical stores to online channels for buying products and services (Schivinski et al., 2022; Donthu et al., 2021). The growth in e-commerce has paved way for online promotion measures, which include digital coupons (Nayal et al., 2021). Such promotions help attract new and retain old customers (Pandey et al., 2020). Social coupons, an innovative digital coupon format, have been used by companies as a key promotional tool. These coupons have seen an upsurge over the years due to the increased use of mobile apps and email (Nayal and Pandey, 2020; Kumar and Rajan, 2012).

Social coupon formats include group buying, prepayment, and daily deals. The group buying phenomenon involves purchases by a network of friends or a random group, attracting greater discounts (Hu et al., 2014). A group-buying deal becomes active once the pre-decided number of buyers or users join the deal. Prepayment is a method of purchasing coupons or deals wherein customers must pay in advance for a deal or coupon to earn substantial discounts over an extended period (Kumar and Rajan, 2012). The majority of the users prefer this type of coupon. Deal of the day or daily deals are offered on a regular basis with varying discounts based on the sales and promotional strategies implemented from time to time (Ieva et al., 2018). Promotions like social coupons mutually benefit both customers and businesses by providing purchase benefits to the former and elevating the customer base and sales for the latter. The increasing interest of customers in online shopping and social media participation provides food and beverage businesses with opportunities to leverage maximum benefits via social couponing, both in the form of economical profits and customer acquisition (Masuda et al., 2022; Dwivedi et al., 2021; Tomar et al., 2018). However, social coupons, though widely distributed, suffer from low redemption rates, and there is a scarcity of research on the factors impacting the redemption of social coupons in the food and beverage sector.

Artificial intelligence (AI) has aided in accelerating the digital revolution over the decennium (Pandey, 2023). Machine learning (ML) enables self-learning and modeling via data mining and provides machines automatic control and decision making with situation-awareness (Kim and Sohn, 2020; Jordan and Mitchell, 2015). These ML algorithms help business models evolve through continuous data learning and recommend informed decisions (Dwivedi et al., 2023a, 2023b; Grover

* Corresponding author.
E-mail addresses: kalyan.pappu.2018@iimmumbai.ac.in (P.K. Ram), npandey@iimmumbai.ac.in (N. Pandey), jinil@iimk.ac.in (J. Persis).

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et al., 2022). While ML algorithms help in providing a curated shopping experience to online customers with recommender systems sharing information regarding nearby facilities, stores, and best-priced hotels, they provide brand managers' insights into a customer's purchase patterns, characteristics, and preferences and help managers devise better marketing strategies (Akter et al., 2022; Tripathi and Pandey, 2018). ML models are extensively being employed by managers to understand market trends, strengthen customer relationships, expand market share, and provide value to the clientele (Pandey, 2023).

The food industry has evolved over decades with technological advancements and continues to show promising growth. Previously, customers used phones to book dine-in seats at restaurants or order takeaways. Today, technology-enabled food order and delivery applications such as Swiggy, Zomato, and Uber Eats allow customers to make informed purchase decisions from a wide spectrum of available options.

ML and AI-based applications have increased customers' engagement and improved their online shopping experience in the food industry. For example, for ordering food online, customers can search for their favorite cuisines from the pre-segregated options on food ordering applications such as Zomato and Swiggy. On selecting the required food type, all rated restaurants offering the item are displayed, with the ones closest to the customer being shown first for quicker delivery. Filters with price ranges, ratings, positive reviews, and many other options are available for customers to choose according to their comfort. The menus are curated with the best combos and deals being shown at the first instance to grab customers' attention. The available coupons and discounts are displayed to the customer as they reach the billing stage. After placing an order, every step of the order from preparation to delivery can be tracked live by the customer.

ML algorithms aid in tracking customers' digital footprints, further supporting businesses with positioning promotions effectively and segmenting target customers efficiently (Ma and Sun, 2020). These algorithms are pivotal to proficiently marketing products and services, leading to customer attraction and retention (Pandey et al., 2019). While ML algorithms generate relevant, timely, and useful promotion schemes in businesses, they can also help predict consumer decisions in response to various promotion schemes and learn their underlying purchase patterns (Chaudhuri et al., 2021). The current study uses ML analysis to explore the factors influencing customers' redemption intentions of social coupons in their food purchases.

The literature on the social couponing phenomenon shows a paucity of research on factors influencing redemption behavior among consumers. Previous studies on social couponing feature a prominent B2B context, whereas this study analyzes the B2C dimension in the social couponing phenomenon. Also, it employs ML for modeling the social coupon redemption decisions, which has hardly been used in earlier studies. Based on the research gaps, the study focuses on two research questions (RQs):

RQ1: *What are the factors influencing social coupon redemption decisions among consumers from the literature and practice perspective?*

RQ2: *What are the relationships between these factors, and how can organizations predict consumers' social coupon redemption decisions by leveraging machine learning models?*

In this context, our study explores the key stimulating factors based on the trends in food e-commerce and examines their role in social coupon redemption decisions. The influence of promotional activities in the food e-commerce sector (e.g., deal of the day) and social commerce cues, from referrals and reviews, on consumers' social coupon redemption decisions are evaluated in this study. Previous studies have presented models on social coupon redemption behavior using well-known theories such as the technology acceptance model (TAM), the theory of planned behavior (TPB), and the valence framework (Jayasingh and Eze, 2009; Kang et al., 2006). Such models test the known relationships among the prevalent constructs assuming static customer behavior. Since consumer behavior evolves over time and is often affected by various internal and external stimuli, these models lack the emerging constructs and relationships that represent a dynamic purchase environment (Nayal et al., 2022).

Consequently, these models lack completeness and robustness, and their predictive power about consumer behavior may not be accurate. In this study, ML modeling and analysis of social coupon redemption decisions, after incorporating the relevant factors, unpack the underlying complex relationships among the factors that influence redemption and accurately predict customer decisions. We use various machine learners such as linear regression, decision trees, random forest, bagged and boosted trees, artificial neural networks, and support vector regression to compare the redemption decisions empirically. The best-fitted models are chosen based on the prediction error measures, i.e., root mean squared error, mean squared error, and mean absolute error. These models are used to derive novel insights about the direct and indirect effects of the factors affecting social coupon redemption decisions.

The rest of the paper is organized in the following way. The next section presents a literature review on social coupon redemption and develops the hypotheses. This is followed by the methodology, including data collection and pre-processing details. After describing the reliability and validity tests, details of the SEM analysis and ML analysis are presented. This section is followed by a discussion of the results and subsequently the implications and conclusions.

2. Literature review and hypothesis development

Research on social coupons is positioned at the intersection of research on digital coupons, promotion techniques, and redemption intention. Digital coupons are a favored choice for many customers as they can be tailored to shopping preferences, are readily available, and are more accessible than traditional coupons (Nayal and Pandey, 2022). Mobile coupons or m-coupons also come under the category of digital coupons. Danaher et al. (2015) analyzed factors influencing mobile coupon redemption among consumers and found that delivery time and location are prominent factors influencing their redemption. The validity period of mobile coupons is also a key driver of redemption choices. Over the years, research on social couponing has been limited to businesses, especially to coupon-providing third parties. Previous research studies (Fang et al., 2023; Pandey and Maheshwari, 2017) have highlighted the role of such couponing in fostering both growth and profits for the companies. These studies have mainly focused on understanding social coupon performance from a business perspective, neglecting the consumer's viewpoint. The dearth of consumer-based insights highlights a potential research gap. Research on redemption-influencing factors is also scarce. The present study uses SEM and ML algorithms to analyze and understand factors influencing customers' social coupon redemption behavior.

There are multiple factors that might attract users to redeem social coupons (Kumar and Rajan, 2012). Zhang et al. (2020) explored the influence of coupon duration and face value on the redemption behavior of customers. The results highlighted the importance of coupon duration and face value in segregating consumers and targeting them. Tang et al. (2018) analyzed consumers' redemption intention of recommended mobile coupons on social network sites. They found that monetary profits and happiness influence mobile coupon redemption intentions. Further, advisor competence, trust, social bonding, and closeness to retailers also play a key role in encouraging conviction in recommendations.

2.1. Referrals

Referrals have gained popularity in the contemporary world of promotions by helping firms harness the benefits from word of mouth and attract new customers (Pandey and Rupnawar, 2022). Referrals are considered more credible by the consumers as they come from known sources (Srivastava et al., 2023). Literature related to referrals highlights that consumers rely on word of mouth and give high weightage to the referrals by other customers for purchase decisions (Dichter, 1966). Businesses also make use of financial incentives and referral programs for boosting referral behavior (Wang and Ding, 2022). The group buying phenomenon in social couponing is fueled by referrals as the person referring is part of close or extended network (Kumar and Rajan, 2012). Most mobile applications pertaining to the food and shopping industry provide customers additional benefits and discounts through social coupons on referring to their friends or family. Referrals also act as a potential tool for businesses to expand their customer base and obtain profitability (Subramanian, 2012). A study by Wang and Ding (2022) analyzed the influence of monetary rewards on product sales in the context of referral programs. The findings explained how the hefty rewards accelerated product sales via referrals. Pereira and Brito (2023) investigated the impact of digital coupon referrals on the purchase intentions of individuals. They found that a higher purchase intention is evident when the product or service is recommended from individuals with strong connections. Therefore, we propose:

H1. Referrals positively influence social coupon redemption behavior.

2.2. Social influence

Social influence is a key strategy employed by several marketing companies and businesses to draw more customers and increase sales (Lai, 2006). It refers to the change in a person's purchase preferences as a result of influence from or interaction with experts or groups (Rashotte, 2007). Consumers' buying behavior is heavily influenced by their interactions with the social environment (Bhukya and Paul, 2023). Social influence has a network effect on businesses in terms of increase in adoption of the products and services. It creates a group effect in the marketplace and strengthens the relationship between the consumers and the firm. It also impacts social couponing by affecting purchase and redemption intention. Kulviwat et al. (2009) studied the direct influence of social influence and the moderation effect of public versus private consumption on the adoption of hi-tech innovations. Their findings showed that social influence positively influences the intention to adopt innovations. Also, publicly accepted innovations lead to stronger ties between adoption intention and social influence. Social influence also leads to social empowerment among consumers in multiple ways (Hanson and Yuan, 2018). Influencer marketing is a prominent strategy that most businesses utilize to engage their customers. Knowledge pertaining to such social influence is extremely beneficial for businesses for targeting consumers (Bhukya and Paul, 2023). Individuals can use their social influence to create a network impact in the marketplace (Lai, 2006). Therefore, we propose:

H2. Social influence from other customers positively influences social coupon redemption.

2.3. Group buying

Group buying reflects the social aspect of couponing, where people come together to purchase products or services to avail of extra discounts. Chen et al. (2009) reported that compared to traditional shopping practices, online group buying was more beneficial to customers. Apart from customers attaining greater discounts, merchants benefit from a higher volume of business (Lee et al.,2016; Singh and Pandey, 2015). Thus, group buying benefits all stakeholders, including buyers, sellers, and coupon aggregator companies (Tai et al., 2012). Group buying is of two types: fixed price and dynamic price. Fixed-price group buying involves websites displaying fixed price deals provided by vendors to group-buying customers. Dynamic price-based group buying involves an initial customer or group leader engaging other potential online customers in group buying and further negotiating with sellers for discounted prices over bulk purchases. In such a dynamic customer environment, group buying works efficiently (Chou, 2019). Fixed-price group buying can endure and sustain in situations of economic recession too (Liao et al., 2012). Hu et al. (2014) investigated the group-buying feature of social coupons by analyzing the clickstream data of Groupon users. The results showed that a tipped deal's information resolved uncertainty in the users' minds and increased the chances of its purchase. It is further understood that group buying has a positive effect on purchase probability and can help reduce the purchase consideration time of users (Hu et al., 2014). Therefore, we propose:

H3. Group buying positively influences social coupon redemption.

2.4. Observational learning

Observational learning provides interesting customer insights. It refers to a customer learning from another customer's purchase history and pattern (Subramanian, 2012). Frequently brought, highly recommended, and best combos are examples of purchase history and older customers' patterns that influence new potential customers to buy the same products and deals. Observational learning influences customers to make judgement about products and services. It also impacts word of mouth (WoM) and sales of the firm (Chen et al., 2012). Observational learning is linked to the cognitive and social learning process. A consumer relying on observational learning would purchase a product or invest in a bond if they learn that the majority of others have also bought the same product or invested in that bond. This makes a potential customer less likely to commit a mistake as the decision is based on past observations (Chen et al., 2012). Previous studies in literature have examined if observational learning can predict herd behavior among consumers. Cai et al. (2009) conducted a field experiment to understand observational learning behavior in the context of restaurant settings. They found that the best dishes ranked by previous customers had a higher demand than other dishes. Tucker and Zhang (2011) conducted an experiment on websites displaying information related to wedding service vendors. They found that displaying webpage visit data by vendors positively influenced future visits by other potential customers, reflecting the trait of observational learning. Therefore, we propose:

H4. Observational learning from other customers positively influences social coupon redemption behavior.

2.5. Deal of the day

Deal of the day is a unique form of promotion that provides heavy discounts to customers for a limited period (Eisenbeiss et al., 2015). It is a promotion that various food delivery applications employ to gain customers' attention and influence their purchase of a particular item. Deal of the day is quite popular in the e-commerce, hospitality, tourism, and beauty industries (Ieva et al., 2018). The limited availability of such deals, which provide substantial discounts, make them a desirable choice among most customers. The savings associated with the product or service purchase is the key motive for consumers to avail themselves of the deal of the day offer. Ieva et al. (2018) found that there is also a hedonic dimension in a deal of the day offering. Consumers look for enjoyment while they avail the deal of the day offers. Kimes and Dholakia (2011) studied the advantages and drawbacks of social couponing and customers' responses to couponing in the context of daily restaurant deals. Daily deals help retain and attract new customers, leading to repeat purchases and increased expenditure on food items (Milwood and Crick, 2021; Pandey and Srivastava, 2013). Deal-of-the-day offers when coupled with an enjoyment dimension impact social coupon redemption (Ieva et al., 2018). Eisenbeiss et al. (2015) examined the impact of time constraints and discounts over the effectiveness of deal-of-the-day promotions using data from the Groupon website. They found that time constraints boost the effectiveness of such promotions for products purchased out of happiness rather than utility. Conversely, discounts enhance the deal effectiveness for utility-based products. Therefore, we propose:

H5. Deal of the day positively influences social coupon redemption intention.

2.6. Prepayment

Social coupons, unlike the regular ones, provide substantial discounts to customers when purchased on a prepayment basis (Nakhata and Kuo, 2017). Prepayment as an aspect of social couponing is beneficial to both customers and businesses. Customers tend to prepay for loyalty programs to earn high discounts and membership benefits, while businesses gain extra customers and multiple orders. Besharat et al. (2021) investigated the influence of prepayment on customers' post-redemption expenditure. A positive correlation was seen between the amount spent on buying the prepaid social coupons and the redemption frequency and amount so long as the time difference between prepayment and redemption was relatively low. In other words, prepayment guarantees the commitment of the buyers and enhances the chances of coupon redemption multi-fold. Customers who are willing to prepay may also share their smart deals on social media platforms, which then helps in promoting the firm and its products (Besharat et al., 2021; Chen and Lin, 2019). A study by Besharat and Nardini (2018) examined impact of prepayment over consumption choices and commitment levels of customers via an experimental design approach. The findings indicated that prepayment boosts expenditure by customers. Therefore, we propose:

H6. Prepayment for deals positively influences social coupon redemption behavior.

2.7. Deal proneness

Deal proneness symbolizes a customer's elevated interest or affinity toward a deal purchase because of the positive impact of the deal on purchase evaluation (Lichtenstein et al., 1990). It is the trait of making purchase decisions based on promotional information (Martínez and Montaner, 2006). Schneider and Currim (1991) classified deal proneness into two types: active and passive. Active deal proneness involves consumers actively searching for different promotions while passive deal proneness refers to consumers limiting their search to particular in-store promotions. Lichtenstein et al. (1997) analyzed the impact of various promotional types on consumer segments in the context of deal proneness. They categorized consumers into different segments based on their deal proneness: deal prone to specific deals and deal prone in general. Various deal types such as rebates, sales, and coupons were employed to determine promotional influence. Findings showed that a segment of customers exhibited a similar level of deal proneness across various deal types. Martínez and Montaner (2006) analyzed the influence of consumers' psychographic traits over deal proneness. The purpose of the survey was to determine proneness toward various promotional aspects like coupons, store flyers, and in-store promotions. The results showed that deal proneness was a dominant behavioral aspect among most price-conscious consumers. Further, it was observed that along with savings, impulsive buying behavior and enjoyment from shopping also influenced deal proneness. Therefore, we propose:

H7. Deal proneness positively influences social coupon redemption behavior.

2.8. Deal pride

Babakus et al. (1988) noted that feelings of pride and satisfaction were potential triggers for coupon redemption and usage. Pride represents a surge in an individual's ego as a result of benefits from valued accomplishments (Lazarus, 2006). It is the positive feeling that consumers experience due to monetary savings post purchase and redemption of promotions. When it comes to promotions, pride symbolizes a consumer's feeling of responsibility to earn a discount (Schindler, 1998). As previously discussed, it is understood that consumers purchasing promotions on prepayment basis tend to be deal prone. While redeeming such promotions, they focus on maximining the benefits, thus satisfying the pride feeling. Customers try to gain the maximum benefit from the item purchased to achieve personal satisfaction (Nakhata and Kuo, 2017). They tend to avoid high-priced items for maximizing benefits by redeeming the social coupons they possess (Nakhata and Kuo, 2017). Therefore, we propose:

H8. Deal pride positively influences social coupon redemption intention behavior.

2.9. Deal eagerness

Deal eagerness represents the anxiety customers experience while waiting for deals to become active (Man et al., 2015). They tend to develop eagerness traits and wait anxiously for new deals and coupons to be available for redemption. Conventionally, social couponing involves three significant stakeholders: businesses, coupon providers, and customers. Post negotiating a promotional deal with businesses, coupon providers disseminate deals to customers. These deals are available for a limited period, which triggers anxiety among potential customers waiting for new deals to be active (Man et al., 2015). Special offers on holidays, festive deals, live sales, and early access deals compel customers to wait eagerly to redeem such deals. Babakus et al. (1988) reported that pride and satisfaction are potential triggers for coupon redemption and usage. Customers try to gain the maximum benefit from the item purchased to fulfill their personal satisfaction (Nakhata and Kuo, 2017). This applies to social coupons as they expect maximum discounts on the given prices. Therefore, we propose:

H9. Deal eagerness positively influences social coupon redemption behavior.

2.10. Perceived risk

Bauer (1960) initially described perceived risk as a mix of both ambiguity and extreme outcomes. It is the level of risk realized or recognized by a consumer in considering purchase decisions (Cox and Rich, 1964). Consumers generally make purchases for fulfilling some buying goals. This process always includes some amount of risk because of the uncertainty of the outcomes. The level of perceived risk of a consumer is a mix two prominent factors: the amount involved with a purchase and the consumer's certainty over winning or losing that amount. The significance of buying goals determines the amount at stake in a situation of perceived risk. Alrawad et al. (2023) explored the impact of significant risk types over a customer's online shopping choices. Structured equation modeling of data collected across three countries showed that information, privacy, and financial risk were prominent risk types influencing the purchase preferences of customers. Pillai et al. (2022) examined the influence of perceived risk and perceived benefit on consumer's buying behavior of online food delivery services. They found that perceived risks and perceived benefits positively influenced the buying behavior of potential consumers. Therefore, we propose:

H10. Perceived risk has a moderating effect on social coupon redemption behavior.

2.11. Consumption frequency

Usage of coupons provides consumers with rewards, motivating them to continue with the product usage (Blattberg and Neslin, 1990). Consumption frequency leads to repeat purchase behavior on e-commerce websites (Huang et al., 2014). It represents number of times a product or service is consumer or purchased by the customers. Arce-Urriza et al. (2017) analyzed the influence of promotions on consumers' buying behavior across both online and offline mediums. Based on data collected from a grocery chain in Europe, the study analyzed how promotions influence offline shopping versus online shopping. Also, consumption frequency is known to show significant moderation effects. It explains how frequent shoppers are more likely to be influenced by promotions than infrequent shoppers (Bawa and Ghosh, 1991). Huang et al. (2014) found that promotions significantly influenced customers' repetitive buying behavior and quality assessment. Further, they observed that consumption frequency showed moderation effects, with promotions influencing the repetitive buying behavior of infrequent

Table 1
Literature review of construct variables.

Construct variables	Author and Year	Research Aim	Key Findings	Gaps if any
Prepayment	Nakhata and Kuo, 2017	To study the consumer avoidance inclinations for products with a unique price framing	The customers avoid redeeming social coupons while purchasing products with a unique price framing especially when buying for enjoyment rather than for useful purposes.	The study focuses solely on hedonic consumption.
	Hanson et al., 2021	Role of customer and discount type on social coupon sharing	Consumers socially close to identified recipients tend to share social coupons more.	Data collection was limited to the North American region.
	Hu and Winer, 2017	Find the effects of the tipping point on the behavior of consumers	Tipping point information increased deal purchases and purchase speed by removing uncertainties regarding the deal's validity.	The study was limited to exploring effects related to learning of individuals from other customer's behavior.
	Kumar and Rajan, 2012	Determine the profitability of businesses through the introduction of social coupons and their impact on customers and merchants	It was not profitable in every business but could act as a prominent marketing method for businesses to attract new customers.	No field experiment was conducted to determine real-time results.
	Nakhata and Kuo, 2014	Analyze the role of consumer reviews on social coupon redemption outcomes	Low variety seekers perceived higher risk and had a lower probability of redeeming coupons from brands that were slightly or not familiar.	Only overall perceived risk was considered to determine influence over social coupon purchase decisions.
Group buying	Zhang et al., 2023	To understand the possession effect of shareable digital coupons	Having sharable digital coupons tends to trigger self-enhancement traits among consumers.	Research is limited to digital coupons.
	Hu et al., 2014	Study the group buying features of social coupons in the context of Groupon	Group buying positively affects the purchase probability and may reduce the purchase decision time of customers.	Considered only one website (Groupon) for data collection.
	Suki and Suki, 2017	Find whether trust issues and risks affect the customer's attitude toward online group buying	Trustworthiness, perceived financial risks, website search time, and product-related information could significantly affect consumers' attitudes toward online group buying.	Smaller sample size.
	Lee et al., 2016	Evaluate the factors that influence customer value and how they affect the intentions of customer participation in group buying	Customer value influenced group-buying participation. Also, factors such as trust in social media, price levels, and website reputation had a more significant influence.	The relationship between the information source and the price levied was not adequately covered. Also, the study neglects the impact of perceived risks.
	Wang and Chou, 2014	Analyze the impact of social influence, characteristics of customers, and systems factors over the intention to repurchase in online group buying websites	Economic buying traits, quality of information, and subjective norms influenced the website's usefulness. In contrast, the quality of the system and similar prior purchase frequency influenced the customers' ease of use.	Research is limited to the Taiwanese region and food products.
	Shi and Liao, 2017	Determine the influence of online consumer reviews over participation in online group buying and consumer beliefs	The online reviews positively influenced customers' familiarity with the intermediaries and perception of effectiveness. Furthermore, customer satisfaction and trust determined continuous participation in online group buying.	The impact of social media on customer trust and satisfaction levels was not covered.
Daily deals	Kimes and Dholakia, 2011	Understand and determine the benefits and detriments of social couponing and its response from the customer in the context of restaurant daily deals	The practices retained older customers, attracted newer ones, increased referrals, and led to customers' inclination to restaurants, where they were ready to come back and pay full price in the future.	The study was limited to customer's experience with daily deals only.
	Ieva et al., 2018	Analyze the key drivers for the adoption of deal-of–the-day shopping choices in young consumers	Enjoyment was observed as the main driving factor. Deal-of-the-day vouchers could leverage higher levels of consumer enjoyment and value to merchants.	Only one deal-of-the-day platform was used for data collection.
Social couponing	Chang et al., 2019	Determine the efficiency of social coupon allocation for optimizing redemption rates in online social networks	Appropriate social coupon allocation to respective users resulted in optimized redemption rates.	Only the simulation method was employed for analysis.
	Subramanian, 2012	Determine the influence of voucher sales information on consumer purchase behavior in the context of social coupons	The relation between coupon profitability and consumer's return probability for similar purchases was quite the opposite. Deal validity information could be counterproductive unless lower limits were set on social coupons and higher consumer return probability.	Outcomes of revealing deal popularity information were limited to the social coupon context only.
	Hanson and Yuan, 2018	Determine whether social coupons lead to the social empowerment of customers	Social couponing phenomenon can lead to the social empowerment of customers.	Focuses on social coupon sharer, but not the receiver.
	Cox, 2015	Determine the experiences of consumers using accommodation deals through social coupon promotions	Customers renting accommodation using deals and promotions were treated equally with the non-deal customers. The customers demanded clarity regarding the offers and conditions of the deals and how they were provided and maintained at the property.	Only studied from an Australian population perspective and limited to the hotel industry.

customers more than that of frequent customers. This is because frequent customers are likely to continue to purchase irrespective of the promotions offered. Therefore, we propose:

H11. Consumption frequency has a moderating effect on social coupon redemption behavior.

Table 1 summarizes the social coupon redemption related variables discussed above. These variables are further analyzed to understand the level of influence each variable has on the redemption levels of customers. Perceived risk and consumption frequency are considered as moderators in the social coupon redemption process.

3. Research methods

The study was conducted in two phases. In the first phase, we used SEM to examine the significance and relationships between exploratory variables and establish the predictability of customers' redemption decision. In the second phase, we explored different machine learners to establish the best-fitting models for customers' redemption decision. The study consisted of the following stages: conceptualization, data collection, modeling, and deployment (Fig. 1). The conceptualization phase involved literature review and identifying the measurement items of social coupon redemption decisions, addressing RQ1. The data collection phase covered pilot study, questionnaire development, sample selection, primary survey, and data pre-processing. The modeling phase focused on developing prediction models. Empirical data were first split into train and test datasets. For selecting the best-fit models, we trained the learners and tuned the hyperparameters using a training dataset for model fitting. This was followed by cross-validation and evaluation of the prediction performance using a test dataset. Finally, in the deployment phase, we evaluated the relationship between the factors and predicted social coupon redemption decisions via the best-fit models, thus addressing RQ2.

Further, the study is based on Saunders's research onion theoretical approach. Every layer of the onion displays information pertaining to each research stage. Researchers are required to traverse from the outer to the inner layer to obtain a clear picture of the complete research process involved (Saunders et al., 2007). The current study is based on epistemology philosophy as it defines acceptable knowledge related to a particular research field and helps provide information post-testing the same. In the first layer of the onion, we implement an interpretivism philosophy, as the current study focuses on understanding consumer behavior toward social couponing and involves social factors influencing the same. After peeling the first layer, we move to the second layer involving a research approach. A deductive approach is selected as the current study involves testing and analysis. The next layer covered research choices. The fourth layer depicts the research strategy, wherein we employ a survey to explore social couponing phenomena in the food sector. The fifth layer delineates the time horizon of the study. The onion's final layer comprises information related to data collection and analysis.

Construct variables were employed to examine their influence on the social coupon redemption process in the food industry. Initially, 95 items were drawn from the extant literature and industry experts inputs. The industry experts comprised of two senior marketing executives and two marketing faculty members with an average experience of over 14 and 18 years, respectively. Seventeen items were removed due to duplication. The experts also recommended removal of twenty-one items due lack of relevance to social coupons and promotion. The final count of items which were used in the questionnaire was 57 (refer appendix Table A1). The next steps involved questionnaire development and survey administration to understand the various dimensions related to social coupon redemption in the food sector.

3.1. Data collection and pre-processing

Primary data were obtained by conducting a cross-sectional survey among online shoppers. A mixed population sample was considered appropriate to investigate the promotional influences among online shoppers. The current study used purposive sampling. The sample

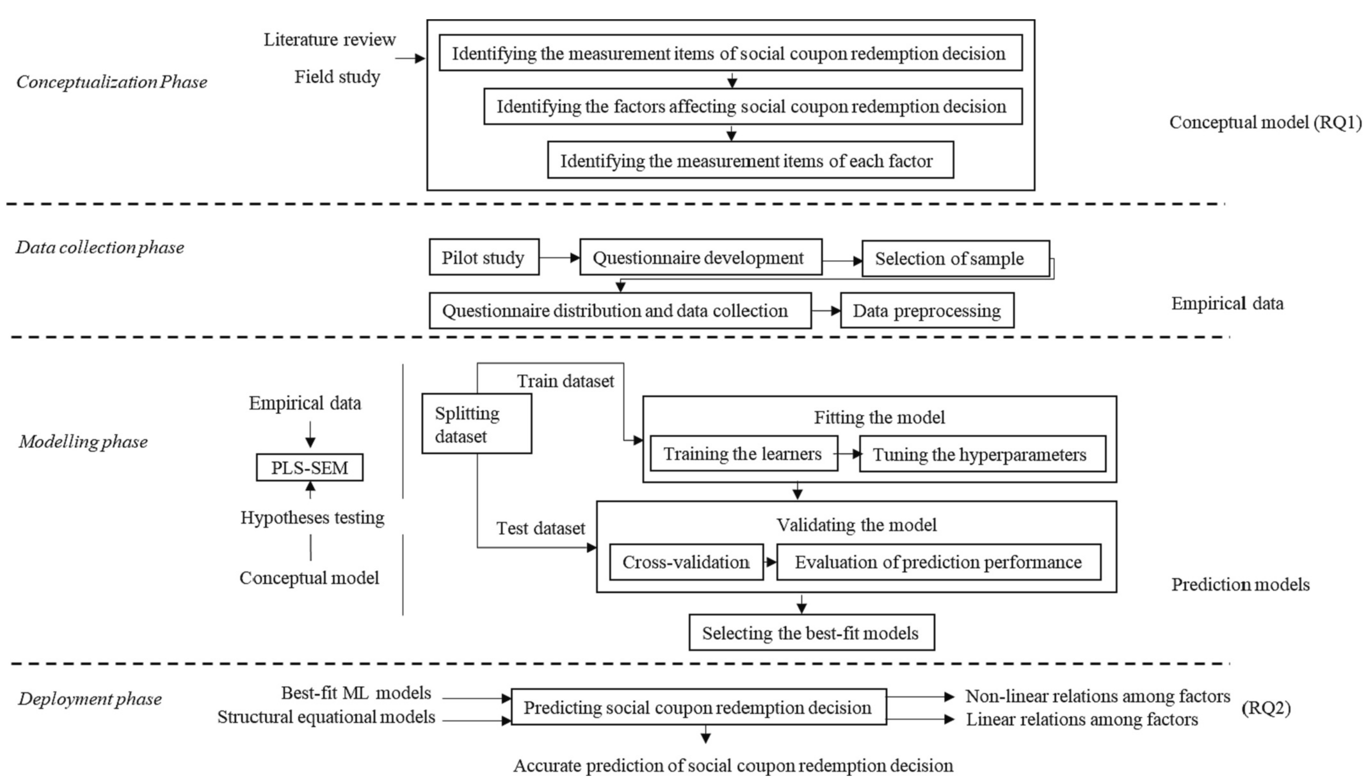

Fig. 1. Research framework.

consisted of online shoppers of varied age groups and with different educational qualifications and employment levels from India. Demographic variables (age, gender, employment status, and work experience) were used to understand the type of shoppers' segment showing potential interest toward redemption of social coupons. After removing invalid responses, we obtained a total of 353 complete responses for further analysis. A seven-point Likert scale (1 denoting "strongly disagree" and 7 denoting "strongly agree") was employed as it is more reliable, and provided multiple data points (Dawes, 2008). The responses were further analyzed using learning algorithms. Of the 353 respondents, about 263 were employed; their work experience ranged from 0.5 to 32 years. The rest were unemployed (jobseeker homemakers, or retired). The study had 187 male and 166 female respondents, distributed over an age range of 18–60 years.

As shown in Table 2, the study focused on 12 variables: 9 independent variables, 1 dependent variable, and 2 moderators. Deal proneness, deal pride, deal eagerness, social influence, referrals, deal of the day, group buying, observational learning, and prepayment formed the independent variables; social coupon redemption was the dependent variable; and perceived risk and consumption frequency acted as the moderators.

3.2. Analysis

Analysis was carried out in two stages. The first stage involved SEM. The second stage consisted of optimization through ML models. SEM was used to test the hypotheses. We developed measurement and path models to determine the flow of relationships among the constructs, which we used for the hypothesis testing. In the next stage, we employed ML analysis to identify prediction models for social coupon redemption decisions. The models with the best fit, which could accurately predict social coupon redemption decisions, were used to derive the direction of the relationships among the constructs. Further, we checked the reliability of the measurement items.

4. Validity

Average variance extracted (AVE) is a measure of the amount of variance that is captured by a construct in relation to the amount of variance due to measurement error. A value higher than 0.5 is acceptable (Fornell and Larcker, 1981).

All values of Cronbach's alpha and composite reliability were greater than the minimum threshold value of 0.7 and hence significant. Further, the AVE values were greater than the minimum value of 0.5 and significant (Table 3). Discriminant validity in the context of the measurement model was assessed by validating the Fornell-Larcker criterion and Heterotrait-monotrait ratio of correlations (HTMT). The Fornell-Larcker criterion is based on a comparison between the squared construct correlations and AVE. It means, on compared to the off-diagonal values of correlation matrix, the underlying values are observed to be lesser, representing that the individual factors show higher correlation with themselves as compared to the inter-item correlation. The Heterotrait-monotrait ratio of correlations is a measure of similarity between latent variables. If the Heterotrait-monotrait ratio value is below one, discriminant validity can be established (Henseler et al., 2015).

Table 4 confirms that the individual factors showed higher correlation with themselves as compared to the inter-item correlation, hence establishing the Fornell-Larcker criterion. Further, all the values were less than the minimum threshold of 1; hence, discriminatory validity was established (Table 5).

5. Structural equation modeling

Standardized root mean square residual (SRMR) is the measure of the deviation of the observed correlation matrix to the model implied correlation matrix. In an ideal scenario, the average difference between the observed and expected correlations is minimal, where smaller values represent a better model fit. A value less than 0.08 is generally considered a good fit (Hu and Bentler, 1999). Our analysis resulted in an estimated value of 0.072, which is less than the minimum threshold and represents a good model fit (Table 6) (Fig. 2).

Group buying, observational learning, prepayment, and deal of the day showed a positive influence over social coupon redemption decisions, with p values less than 0.5 (Table 7). On the contrary, referrals and social influence showed no significant influence over social coupon

Table 2
Construct variable definition.

Items	Author reference	Definition
Deal Proneness (DP)	Ieva et al., 2018	The eagerness and inclination of customers toward purchasing a product due to attractive deals.
Deal Eagerness (DE)	Man et al., 2015	An anxious feeling that customers experience during the wait time for new coupons to be available.
Deal Pride (DR)	Nakhata and Kuo, 2017	Customers tend to redeem most of the coupons to increase their pride in saving money.
Social Influence (SI)	Hu et al., 2014	Influence from socially empowered people, celebrities, and social sites.
Observational Learning (OL)	Subramanian, 2012	Learning from deal purchase levels of customers that could influence the other potential customers to make similar purchases.
Group Buying (GB)	Hu et al., 2014	A way of buying similar deals or vouchers by a group of people to obtain greater substantial discounts equally by every person involved in the deal.
Referrals (RE)	Subramanian, 2012	Referring deals to other customers.
Deal-of-the-day (DD)	Ieva et al., 2018	Deals which are available only for a day or a period.
Prepayment (PP)	Nakhata and Kuo, 2017; Kumar and Rajan, 2012	It is a method of buying coupons or deals wherein customers must pay in advance for a deal or coupon to obtain substantial discounts over an extended period.
Social Coupon Redemption (SC)	Kumar and Rajan, 2012	Using coupons to receive a discount or rebate.
Perceived risk (PR)	Dowling, 1986	An uncertainty the customer experiences while purchasing a product or service.
Consumption frequency (CF)	Nayal and Pandey, 2020	The number of times a product or service is consumed or purchased.

Table 3
Convergent validity.

	Cronbach's alpha	Composite reliability (rho c)	Average variance extracted (AVE)
Consumption frequency	0.871	0.912	0.722
Deal of the day	0.826	0.878	0.590
Deal eagerness	0.904	0.929	0.723
Deal proneness	0.766	0.842	0.519
Deal pride	0.706	0.81	0.561
Group buying	0.785	0.853	0.538
Observational learning	0.746	0.84	0.569
Prepayment	0.825	0.878	0.590
Perceived risk	0.741	0.78	0.577
Referrals	0.822	0.882	0.653
Social coupon redemption	0.818	0.873	0.581
Social influence	0.855	0.892	0.579

Table 4
Fornell-Larcker criterion.

		1	2	3	4	5	6	7	8	9	10	11	12
1	Consumption frequency	0.849											
2	Deal of the day	0.66	0.768										
3	Deal eagerness	0.693	0.62	0.851									
4	Deal proneness	0.692	0.56	0.69	0.721								
5	Deal pride	0.662	0.62	0.611	0.639	0.679							
6	Group buying	0.637	0.745	0.48	0.552	0.586	0.733						
7	Observational learning	0.754	0.585	0.474	0.604	0.641	0.62	0.754					
8	Prepayment	0.754	0.684	0.755	0.675	0.699	0.598	0.656	0.768				
9	Perceived risk	0.246	0.411	0.111	0.169	0.252	0.297	0.278	0.194	0.614			
10	Referrals	0.683	0.78	0.568	0.606	0.572	0.685	0.655	0.672	0.299	0.808		
11	Social coupon redemption	0.793	0.643	0.681	0.708	0.665	0.642	0.724	0.781	0.219	0.64	0.762	
12	Social influence	0.626	0.827	0.569	0.481	0.631	0.762	0.561	0.621	0.369	0.683	0.574	0.761

redemption decisions.

Deal proneness and deal eagerness showed positive relationships with social coupon redemption (Table 8). Deal pride did not exhibit a significant relationship with social coupon redemption. Further, the deal initiators showed significant relationships with the deal activators. No significant moderation effects were observed from either perceived risk or consumption frequency (Table 8).

6. Machine learning analysis

ML-based approaches are being increasingly used in marketing to understand and interpret a survey dataset effectively (Van Giffen et al., 2022; Ramirez et al., 2019). Supervised learning methods are used to perform regression analysis, relating one or more predictor variables with a particular response variable. We classified the dataset into training and testing instances, which were used for fitting and validation processes. This approach involves fitting a regression curve that almost rightly maps the values of predictor variables to the corresponding value of the response variable for every training instance. While line fitting is traditionally performed using ordinary least squares (OLS) regression, non-linear methods are also seen in the literature, like support vector regression (SVR), artificial neural network (ANN), and tree-based methods. The existence of linearity/non-linearity and interactions among the predictor variables are likely to have an impact on the predictive power of social coupon redemption behavior. While the deviation of linearity among the predictor variables is difficult to realize, there are a few studies in which the predictor variables governing a particular behavioral intention are likely to deviate from linearity. For example, Islam and Nahiduzzaman (2022) explored ML methods and compared model performance with the linear method. In the validation process, the fitted and the actual outcomes of the test instances were used to determine squared deviations, which were then used to evaluate error measures such as mean absolute error, mean square error, and root mean square error.

In this study, to model online shoppers' social coupon redemption decisions, five response variables were identified and relationships with 52 predictor variables were studied (Refer appendix Table A2). We used linear and non-parametric methods for fitting each aspect of the social coupon redemption behavior as a function of the predictor variables. We explored frequently used algorithms such as decision tree, random forest, bagged and boosted trees, artificial neural network, and support vector machine.

We first obtained the baseline statistical fit using the multiple regression method, and the predictive performance was evaluated. Generally, an OLS estimator is used in multiple regression to determine the linear equation's coefficient relating the predictor variables to the response variable at minimum residual error. Let SCR_i denote the vector of the response variable, where i varies from *1* to *5,* and the predictor variables are denoted by X_j, where j varies from 1 to 52. The linear fit obtained using OLS estimates was as follows: $\widehat{SCR}_i = \widehat{\beta_0} + \sum_{j=1}^{52}\widehat{\beta}_j X_j \forall i$, where β is the vector of regression coefficients, and $\widehat{\beta}$ is the estimate of the regression coefficient such that $\widehat{\beta} = argmin_{\beta}\left[\sum_{k=1}^{n}\left(SCR_i - \beta_0 - \sum_{j=1}^{52}\beta_j X_j\right)^2\right]$ where k varies from *1* to n training samples. We developed five models for each response variable considered in the study. The fitted models were validated with test instances, and the error measures were evaluated.

We also explored non-linear methods to improve the predictive power of the models. A regression tree was used to analyze the data and construct prediction models for each response variable. Typically, regression trees identify the decision rules, consisting of ranges of values, for various combinations of predictors that lead to a particular range of a response variable. The regression tree is made of decision nodes where a predictor variable is examined and bifurcates into branches. The tree starts with a root node for the complete dataset from which branches bifurcate. The nodes that do not bifurcate further are called leaf nodes, where the tree terminates. The mechanism of building a regression tree involves iterative splitting of training instances at every non-leaf node into two partitions that are more homogenous compared to the current set of instances based on a partial decision rule pertaining to a predictor variable. At every leaf node, a homogenous subset of instances remains, and along each branch that starts from the root node to a leaf node, a decision rule is made. The goodness of the fit yielded by the decision tree regressor is evaluated based on the homogeneity of instances at every leaf node, generally called the impurity measure. Entropy, gini-index, and information gain are commonly used impurity measures. The right choice of a prediction variable and instances of split at every decision node lead to the construction of an accurate decision rule across a branch, which is governed by the error minimization function, given as $S = argmin_s\left[\sum_{j=1}^{n}\left(\widehat{SCR}_j - SCR_j\right)^2\right]$, where S denotes the splitting criterion $\{X_{j^*} \in (l,u)\}$. Here, j^* denotes the predictor in the range (l,u) that splits the instances into homogenous partitions with minimum error. Regression trees often either tend to overfit decision rules, satisfying every training instance, or underfit decision rules, without focusing on the training instances properly. The ability to learn decision rules generally depends on the depth of the tree and the minimum instances required to set a node as a leaf or a non-leaf node, which are important hyperparameters to be set after proper finetuning. We used a grid search algorithm to finetune these hyperparameters (Abbasimehr et al., 2020; Lujan-Moreno et al., 2018). Ensemble learning using bootstrapping, bagging, and boosting strategies was introduced in the regression trees (Galvani et al., 2021; Sipper and Moore, 2022). Random forest regressor adapts bagging that involves parallel independent learning through multiple bootstrapped feature subsets and aggregates them to generalize a prediction rule. Boosting involves sequential learning through multiple dependent feature subsets and then

Table 5
Heterotrait-monotrait ratio of correlations (HTMT).

	Consumption frequency	Deal of the day	Deal eagerness	Deal proneness	Deal pride	Group buying	Observational learning	Prepayment	Perceived risk	Referrals	Social coupon redemption	Social influence
Consumption frequency												
Deal of the day	0.774											
Deal eagerness	0.779	0.706										
Deal proneness	0.846	0.688	0.836									
Deal pride	0.838	0.806	0.765	0.846								
Group buying	0.756	0.826	0.546	0.693	0.785							
Observational learning	0.825	0.747	0.56	0.784	0.841	0.825						
Prepayment	0.837	0.825	0.842	0.848	0.815	0.734	0.827					
Perceived risk	0.228	0.623	0.181	0.233	0.367	0.475	0.303	0.192				
Referrals	0.804	0.844	0.649	0.75	0.747	0.846	0.839	0.812	0.466			
Social coupon redemption	0.831	0.779	0.786	0.841	0.845	0.795	0.824	0.84	0.216	0.778		
Social influence	0.718	0.84	0.635	0.576	0.806	0.829	0.696	0.729	0.531	0.811	0.671	

Table 6
Model fit.

	Saturated model	Estimated model
SRMR	0.068	0.072
d_ULS	10.1	11.097
d_G	4.088	4.22
Chi-square	3400.891	3459.354
NFI	0.669	0.661

aggregating them to generalize prediction outcomes. We explored random forest regressor, adaptive bagging, and extreme gradient boost techniques for implementing these strategies.

Artificial neural network (ANN) analysis is widely used for solving various prediction problems in business applications (Marques et al., 2014; Nan et al., 2022). ANN consists of input, hidden, and output neurons, where the values of each predictor variable of a training instance are fed into the network through input neurons. The actual value of the response variable is made available to all hidden neurons, and the predicted value for the response variable is obtained from the output neurons, which should be as close as possible to the actual value. Multiple hidden layers, each having a specific number of hidden neurons, are often used for better generalization capability. Training instances are repeatedly presented to the network. Through each activated hidden neuron, the weighted values of the predictor variables are added with a bias and transferred using an appropriate activation function to the subsequent hidden layer. A hidden neuron, h, takes a training sample, k, and generalizes an outcome, y, based on the activation function, f as follows: $y_h = f\left(\sum_{j=1}^{52} w_{kj}X_{kj} + \theta_h\right)\forall k = 1..n$ samples. The weights and biases are learned through backpropagation with subsequent k's such that the deviation between the predicted and the actual value of the response variables is minimized through the gradient descent approach. The gradient is represented as $\nabla_\theta L(\theta|y, X) = \sum_{k=1}^{m} \nabla_\theta \left(f(X_k, \theta) - y_k\right)^2$, where m denotes the batch size, which is backpropagated, and weights and biases are updated as follows: $\theta' = \theta - \alpha\nabla_\theta L(\theta|y, X); W' = W - \alpha\nabla_W L(W|y, X)$ respectively, where α denotes the learning rate.

Support vector regression (SVM) is another widely utilized supervised learning method for predicting consumer behavior (Al-Mashraie et al., 2020; Chen et al., 2012). SVM attempts to identify a hyperplane in the feature space that maps a value for the response variable when provided with values for predictor variables. The problem is to identify hyperplane p^* represented as $y_{p^*} = f\left(\sum_{j=1}^{52} w_{kj}X_{kj} + \theta_p\right)\forall k = 1..n$ samples such that the margin from the nearest instance in the feature space is the maximum. Kernel functions such as linear, polynomial, sigmoid, and radial basis functions are used to generate hyperplanes that iteratively aim to minimize the loss at every subsequent training instance. The hyperplane is represented with a set of support vectors located at a margin from the hyperplane. Every iteration weight vector is learned using a gradient descent approach with regularization. We found the optimal hyperparameters for each non-parametric learning method using a grid search algorithm. The social coupon redemption behavior of online shoppers was predicted using these methods, and the best fit was selected by comparing the performance of the models.

6.1. Model evaluation and selection

We analyzed the data using multiple methods: linear regression (LM), artificial neural network (ANN), support vector regression (SVR), decision tree (DT), random forest (RF), adaptive bagging (adabag), and extreme gradient boosting (XGB). The method that yielded an accurate fit was selected. Training and testing datasets were split using k-fold cross-validation (with $k = 16$) (Jung, 2018). Using k-fold cross-validation, we sampled sufficient instances for the training and testing

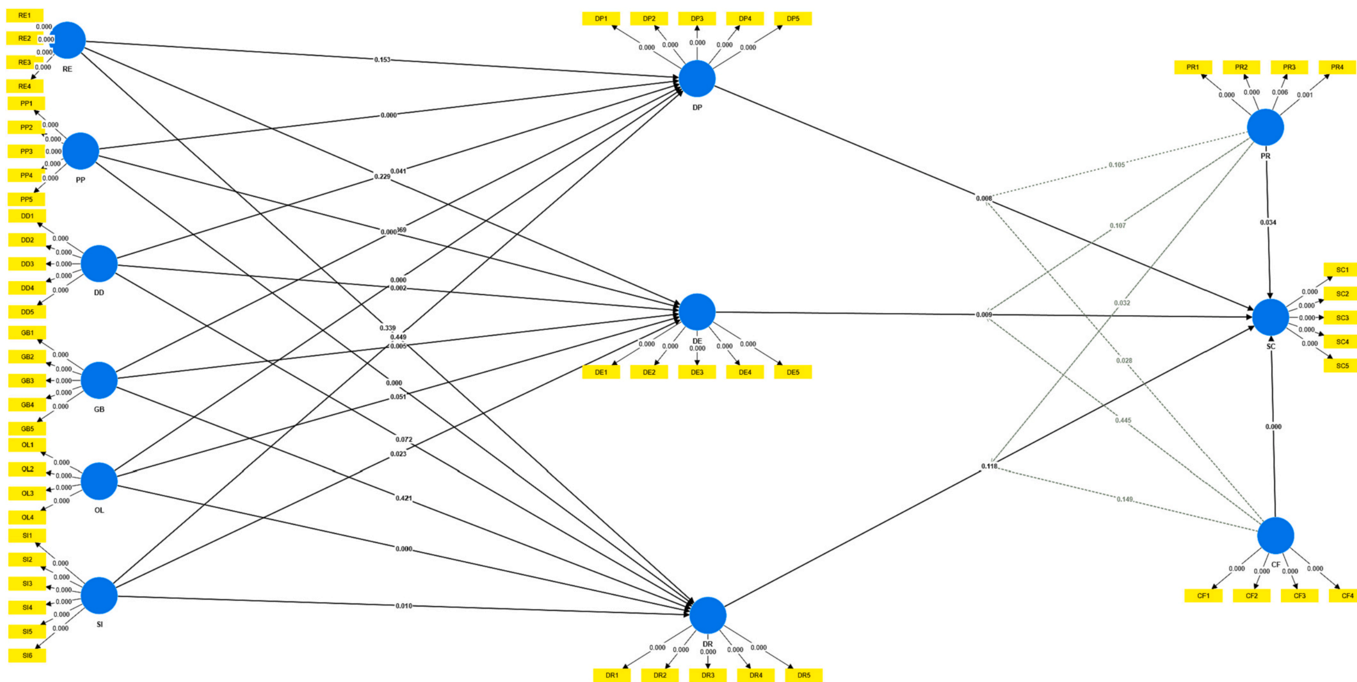

Fig. 2. Path model.

Table 7
Total indirect effects.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	*P* values
Deal of the day → Social coupon redemption	0.066	0.061	0.027	2.437	0.007
Group buying → Social coupon redemption	−0.044	−0.035	0.027	1.658	0.049
Observational learning → Social coupon redemption	0.071	0.07	0.026	2.716	0.003
Prepayment → Social coupon redemption	0.173	0.161	0.046	3.741	0.001
Referrals-> Social coupon redemption	−0.002	−0.001	0.023	0.091	0.464
Social influence → Social coupon redemption	0.039	0.033	0.025	1.577	0.057

phases. The optimal splitting ratio for these datasets was determined iteratively by exploring different splitting ratios, and the results are presented in the appendix (Refer Figs. A1 to A5). We performed *k*-fold cross-validation in which random samples of *k*-trials were generated by varying the splitting ratio from 3:7 to 9:1. The average of the mean squared error

(MSE) across *k*-trials was made for each splitting ratio. Figs. A1 to A5 (in Appendix) show the ratio at which MSE is minimum for each model, and these ratios were further used to with the training and testing datasets. We selected the best split that yielded a high predictive performance. A training dataset typically contains known instances that are used to obtain the fitted model. During the testing phase, unknown instances are provided to the fitted model for evaluating the fitted values, which are compared with the actual values. The deviation of the fitted values from the actual values is used to compute the error measures. The results of the computed error measures in this study—mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE)—are presented in Table 9. Of all the methods, the decision tree learner had the least error measures. We performed a grid search (Alaka et al., 2018) to finetune the hyperparameters of the decision tree, and the results are presented in the appendix (refer appendix Table A3).

We used a decision-tree regressor to predict the social coupon redemption outcomes from the values of the predictor variables by analyzing the dataset. The prediction rules are presented in Figs. 3, 4, 5, 6, and 7. The seven-point Likert scale helped understand the degree of customers' agreement with the various factors impacting social coupon redemption. Each pointer on the scale represented a certain degree of acceptance (1 = strongly disagree, 2 = disagree, 3 = somewhat disagree, 4 = neither agree nor disagree, 5 = somewhat agree, 6 = agree, and 7 = strongly agree). The social coupon redemption model explained the degree to which customers are inclined to purchase and redeem such coupons for substantial discounts on the products or services purchased. In the model, SC1–SC5 represented social coupon redemption items. Fig. 3 shows that the model utilized only six variables for representing SC1. If the perception about DP1 was less than 5 and DD3 was less than 4, then the model predicted SC1 as 3, else as 5.

On the contrary, with DP1 greater than 5, CF4 less than 5, and DP5 less than 6, the model predicted SC1 as 4, else 5. Also, with CF4 greater than 5, PR2 greater than 6, and DP5 less than 7, the model predicted SC1 as 7, else 4. When PR2 was less than 6, SC1 was observed to be 6. Fig. 4 shows that about 17 variables were employed by the model for assessing the role of these variables over SC2. If CF3 was less than 4, then the perception for SC2 was observed to be 3. With CF3 greater than 4, RE2 greater than 6, GB2 greater than 4, and DR2 greater than 6, the SC2 value was predicted to be 6. Similarly, other branches depicted the degree of influence of the predictors over the response variable SC2.

Fig. 5 confirms that the model used about 11 variables for prediction. It is understood that a value of CF2 less than 4 and PP2 less than 3 results in SC3 as 2, else as 4. Further, with CF2 greater than 4, DP1 greater than 5, and PR4 greater than 7, SC3 was observed to be 6. Similarly, other potential influence levels were observed through the branches. Fig. 6 shows the use of 16 variables for examining predictions about SC4. If

Table 8
Total effects.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Consumption frequency → Social coupon redemption	0.402	0.416	0.079	5.091	0.001
Deal of the day → Deal eagerness	0.196	0.19	0.067	2.918	0.002
Deal of the day → Deal proneness	0.131	0.128	0.076	1.74	0.041
Deal of the day → Deal pride	0.108	0.113	0.074	1.464	0.072
Deal of the day → Social coupon redemption	0.066	0.061	0.027	2.437	0.007
Deal eagerness → Social coupon redemption	0.211	0.19	0.089	2.383	0.009
Deal proneness → Social coupon redemption	0.143	0.142	0.059	2.419	0.008
Deal pride- > Social coupon redemption	0.057	0.055	0.048	1.185	0.118
Group buying → Deal eagerness	−0.19	−0.176	0.074	2.549	0.005
Group buying → Deal proneness	−0.024	−0.021	0.073	0.334	0.369
Group buying → Deal pride	−0.014	−0.01	0.071	0.2	0.421
Group buying → Social coupon redemption	−0.044	−0.035	0.027	1.658	0.049
Observational learning → Deal eagerness	0.093	0.095	0.057	1.637	0.051
Observational learning → Deal proneness	0.245	0.246	0.066	3.742	0.002
Observational learning → Deal pride	0.294	0.288	0.062	4.725	0.001
Observational learning → Social coupon redemption	0.071	0.07	0.026	2.716	0.003
Prepayment → Deal eagerness	0.522	0.519	0.053	9.795	0.002
Prepayment → Deal proneness	0.328	0.327	0.058	5.648	0.001
Prepayment → Deal pride	0.284	0.283	0.061	4.642	0.001
Prepayment → Social coupon redemption	0.173	0.161	0.046	3.741	0.002
Perceived risk → Social coupon redemption	−0.099	−0.104	0.055	1.822	0.034
Referrals → Deal eagerness	−0.052	−0.048	0.07	0.743	0.229
Referrals → Deal proneness	0.075	0.078	0.073	1.022	0.153
Referrals → Deal pride	−0.029	−0.027	0.071	0.414	0.339
Referrals- > Social coupon redemption	−0.002	−0.001	0.023	0.091	0.464
Social influence → Deal eagerness	0.148	0.14	0.074	1.988	0.023
Social influence → Deal proneness	−0.009	−0.008	0.067	0.129	0.449
Social influence → Deal pride	0.156	0.152	0.067	2.311	0.01
Social influence → Social coupon redemption	0.039	0.033	0.025	1.577	0.057
Perceived risk × Deal proneness → Social coupon redemption	−0.101	−0.08	0.081	1.254	0.105
Consumption frequency × Deal pride- > Social coupon redemption	0.076	0.061	0.073	1.042	0.149
Perceived risk × Deal eagerness → Social coupon redemption	−0.109	−0.085	0.087	1.242	0.107
Consumption frequency × Deal proneness → Social coupon redemption	−0.132	−0.12	0.069	1.909	0.028
Consumption frequency × Deal eagerness → Social coupon redemption	−0.011	−0.006	0.079	0.139	0.445
Perceived risk × Deal pride → Social coupon redemption	0.146	0.12	0.079	1.849	0.032

CF4 was less than 5, DD3 was greater than 3, and DD1 was greater than 5, then the model predicted SC4 to be 5, else 4. On the other hand, if CF4 was greater than 5, DE2 was greater than 5, DP5 was greater than 7, and SI6 was greater than 4, then the model predicted SC4 to be 6. The remaining branches depicted other significant relationships and their degree among the variables. Fig. 7 illustrates that the model utilized a total of 14 variables to explain the prediction related to SC5. When DP1 was less than 5 and SI3 was less than 3, the SC5 value was predicted to be 1, else 5. If DP1 was greater than 5, CF2 greater than 4, and SI7 greater than 7, then the model predicted SC5 as 6. Similarly, all other connections and their degrees were depicted through the various branches.

7. Discussion

While studies have covered the benefits of social couponing for coupon providers, there has been a lack of research on understanding social couponing from a customer's perspective. In fact, there is hardly any research on the factors that drive customers when it comes to the redemption of food-related social coupons. The current study explores the influence of potential factors on customers' social coupon redemption in the food industry through ML algorithms. According to the available literature, businesses are leveraging artificial intelligence (AI), including generative AI and ML models, to explore customers' behavioral patterns through their online shopping data (Dwivedi et al., 2023c, 2023d; Koohang et al., 2023; Ooi et al., 2023). These ML models are being utilized to provide tailor-made experiences to customers for their future shopping sessions. This study has leveraged ML algorithms to explore and understand the influence of each potential factor on customers' social coupon redemption behavior. It also examines the role of moderators in customers' redemption behavior using ML models.

The analysis showed that 70 % of individuals with high deal proneness, high consumption frequency, and lower perceived risk were more likely to redeem social coupons. Also, only 5 % of those who were

Table 9
Performance of the fitted models.

Dependent Variables	SC1			SC2			SC3			SC4			SC5		
Performance metrics	*RMSE*	*MSE*	*MAE*	*RMSE*	*MSE*	*MAE*	*RMSE*	*MSE*	*MAE*	*RMSE*	*MSE*	*MAE*	*RMSE*	*MSE*	*MAE*
LM	0.880	0.774	0.638	0.936	0.877	0.716	1.091	1.190	0.850	1.021	1.042	0.793	1.125	1.266	0.923
DT	0.746	0.556	0.515	0.909	0.827	0.686	1.033	1.068	0.854	0.914	0.836	0.663	1.001	1.003	0.772
RF	0.789	0.623	0.583	1.097	1.204	0.888	1.294	1.674	0.981	1.033	1.067	0.859	1.053	1.110	0.826
Adabag	0.951	0.904	0.660	1.037	1.075	0.768	1.181	1.394	0.915	1.216	1.480	0.951	1.283	1.646	0.984
XG Boost	1.262	1.593	0.955	1.068	1.141	0.848	1.079	1.164	0.885	1.116	1.246	0.888	1.099	1.207	0.896
ANN	1.281	1.640	0.686	1.137	1.292	0.831	1.215	1.477	0.963	1.228	1.508	0.990	1.133	1.285	0.937
SVM	1.178	1.387	0.742	1.038	1.077	0.824	1.366	1.867	1.053	1.236	1.528	0.925	1.322	1.746	1.005

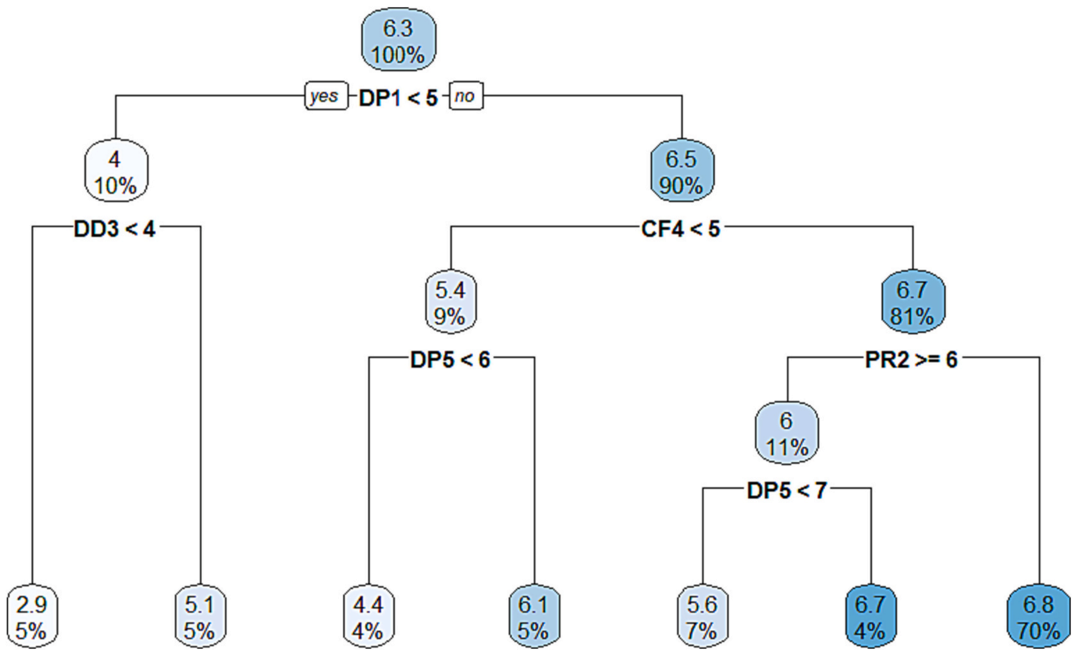

Fig. 3. Best fit model representing Social Coupon redemption 1.

highly deal prone but shopped less frequently were inclined toward social coupon redemption. Furthermore, another 5 % of those who displayed less deal proneness but were attracted to deal of the day or daily deals intended to participate in social coupon redemption (Fig. 3).

According to the results, 18 % of individuals exhibiting high deal pride, participating extensively in group buying, engaging in coupon and deal referrals regularly, and having higher consumption frequency were more likely to redeem social coupons. Further, only 10 % of those displaying high consumption frequency and affinity toward prepayment and referrals were expected to redeem social coupons. Among the participants, 16 % with high referrals, prepayment, perceived risk, excessive consumption frequency, yet moderate group buying traits were more likely to redeem social coupons (Fig. 4).

Further, 23 % of those exhibiting higher deal pride and deal proneness, increased consumption frequency and referrals but moderate perceived risk and social influence were likely to redeem social coupons. Only 11 % of participants with less perceived risk, excessive deal proneness and consumption frequency, higher referral behavior yet moderate social influence tended to redeem social coupons. Further, only 9 % with similar traits and higher deal eagerness were observed to participate in social couponing (Fig. 5).

Among the participants who exhibited increased deal proneness and deal eagerness, high consumption frequency, and average social influence, 18 % tended to redeem social coupons. Further, 12 % with excessive deal eagerness and deal proneness, higher consumption frequency, and moderate involvement in group buying were inclined to redeem social coupons. Only 10 % of those highly inclined toward prepayment, exhibiting excessive deal proneness and consumption frequency but average levels of deal eagerness and referral behavior were likely to redeem social coupons. Similarly, only 10 % of those showing higher deal proneness and consumption frequency had positive impact from social influence, but less eagerness toward deals were keen on social couponing (Fig. 6).

High deal proneness and increased affinity toward social influence and consumption frequency influenced only 10 % to indulge more in social couponing. Among those showing traits of observational learning and deal proneness, with high consumption frequency but lower interest toward social influence and deal pride, only 8 % participated in social couponing (Fig. 6). Among participants with similar traits, high and moderate impacts of social influence prompted greater redemption behavior in 16 % and 14 % of customers. Only 6 % of those with higher deal proneness, observational learning, and consumption frequency and prevalent social influence were likely to engage in social coupon redemption (Fig. 7). Among participants with similar traits but with less social influence 7 % were likely to redeem social coupons. Further, 5 % with increased interest in deal proneness and consumption frequency with positive influence from observational learning and social influence were likely to engage actively in social couponing (Fig. 7). Five percent of participants with similar behavior and higher interest toward daily deals were likely to be involved in social coupon redemption. Only 4 % of those with higher consumption frequency and deal proneness but less impact of observational learning and social influence tended to redeem social coupons. Also, among participants who were highly deal prone yet rarely purchased coupons or deals, 5 % were likely to redeem social

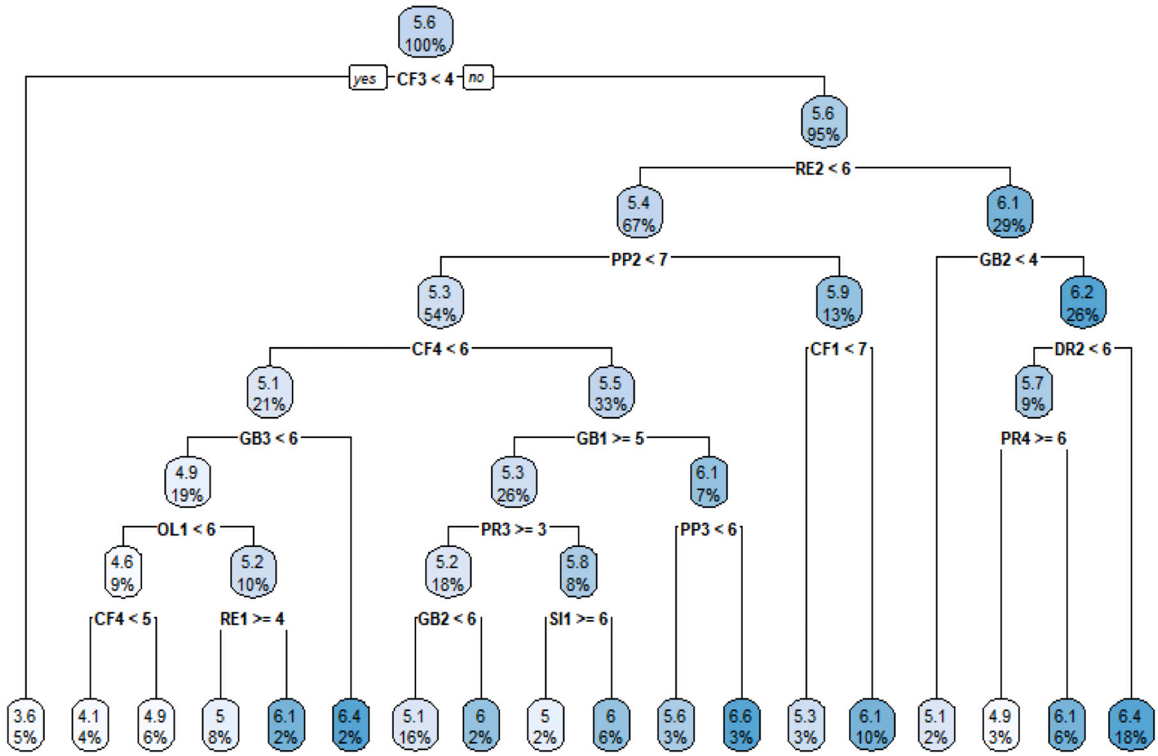

Fig. 4. Best fit model representing Social Coupon redemption 2.

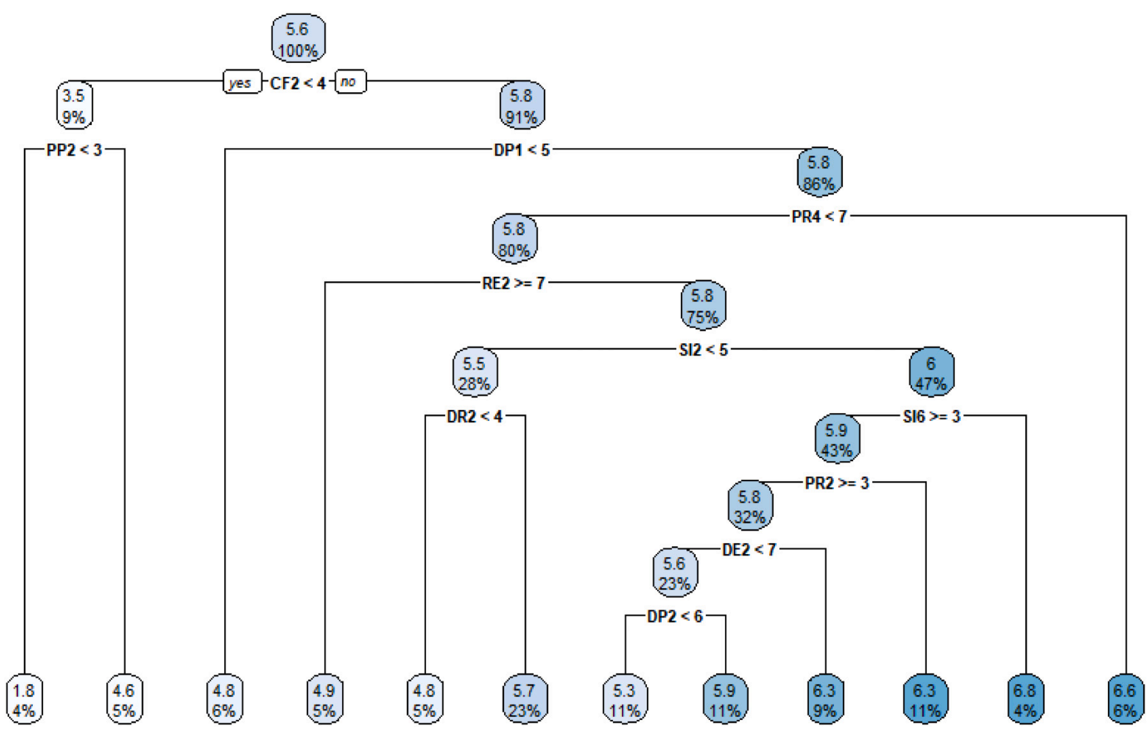

Fig. 5. Best fit model representing Social Coupon redemption 3.

coupons. Among those who were less deal prone yet had positive social influence, 6 % were likely to redeem social coupons more (Fig. 7).

The above data suggests that certain variables exert significant influence over social coupon redemption within the food industry, confirming the effectiveness of certain promotions on customers. While participants of all ages were interested in couponing, participants aged 25–29 years showed the highest participation, which suggests that younger customers have a greater interest in food-related social coupons. Moreover, a higher percentage of employed participants were active users of food coupons, indicating that individuals with financial stability tend to show greater interest in social couponing. Owing to the use of ML algorithms, significant mediation and moderation effects were

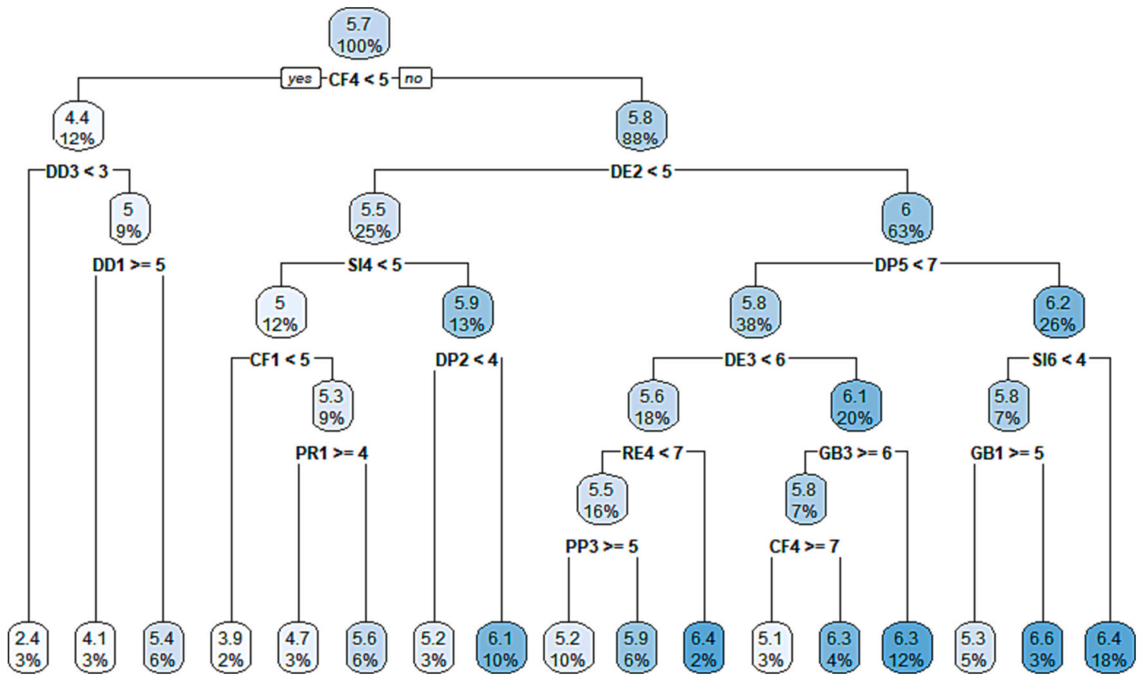

Fig. 6. Best fit model representing Social Coupon redemption 4.

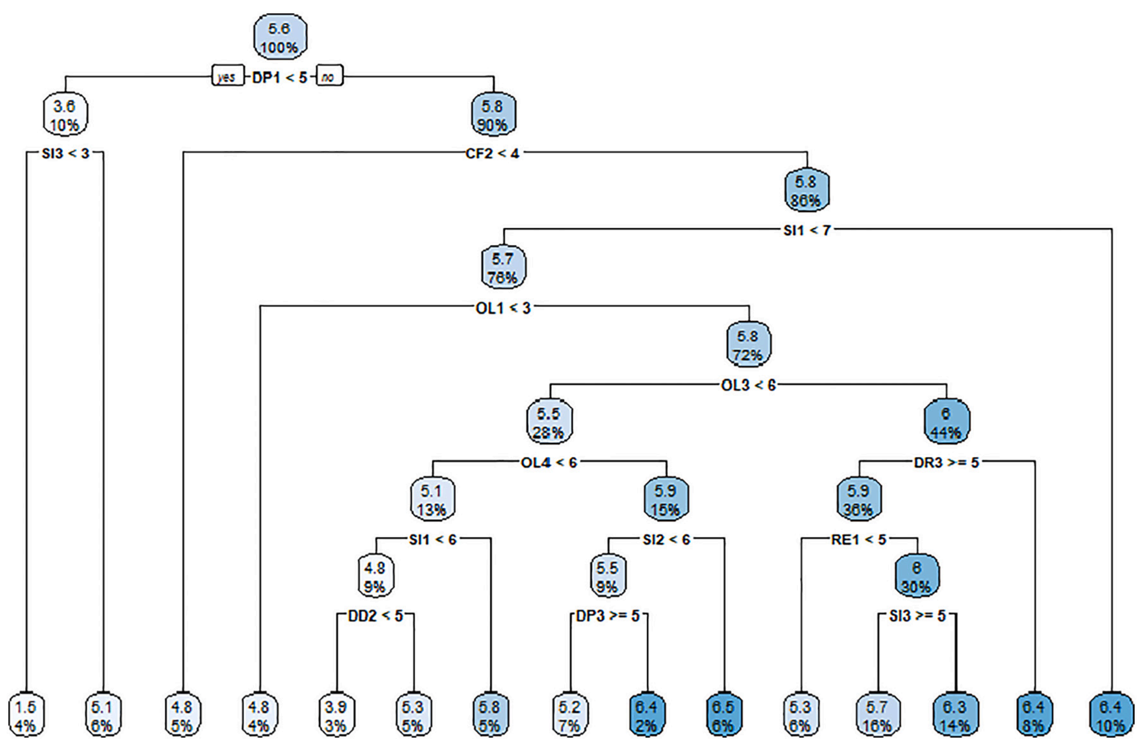

Fig. 7. Best fit model representing Social Coupon redemption 5.

recorded through the binary trees. Consumption frequency had a moderating influence over individuals' purchase and redemption choices. Perceived risk also significantly affected redemption choices, highlighting that individuals experience a certain amount of risk when sharing information for purchasing or redeeming social coupons. Thus, it is evident that social coupons as a promotional feature influence customers' purchase preferences in the food industry.

7.1. Contributions to theory

The detailed decision-tree analysis offers valuable insights into the influence of each variable on social coupon redemption decisions. The best-fit model for each response variable clearly identifies their significant influence over social coupon redemption by consumers. Among the predictor variables, deal proneness, deal pride, and deal eagerness have substantial effects on redemption. Additionally, prepayment traits and social influence play a key role in drawing consumers to social couponing in the food sector. Referrals from peers and family members also influence consumers' preferences for social coupons. The moderation effects of consumption frequency are noteworthy. High frequency consumers are more likely to participate in the social couponing process and are more confident about sharing deal information with friends and family. Such users are also comfortable with sharing their personal information to redeem social coupons. These variables and moderation items provide a deeper understanding of the coupon redemption process and its business-related prospects.

7.2. Contributions to practice

Businesses constantly seek opportunities to enhance their customer base and profitability. In this context, social coupons are a valuable promotional feature. Guided by the findings of this study, practitioners can focus on select variables while designing new promotional features and coupons and thus increase their sales. The results of the ML analysis are promising in that they show how businesses can exploit technological advances not only in sales but also in promotional contexts. The survey results showed that many young and employed people are highly prone to social coupon offers. Since the younger generation is attracted to social media platforms, organizations should float social coupons on platforms that are frequently visited by the youth, such as Instagram, Meta, and X and popular gaming sites like Twitch, Roblox, and Nintendo. This segment of consumers looks for large discounts and benefits both through referrals and membership programs. They tend to purchase together to acquire products and services at a better price. Thus, prepayment, group buying, social influence, referrals, and observational learning are prominent factors influencing younger individuals.

Additionally, our results found that employed individuals tend to use social coupons, usually to maximize their profits for the money paid. They tend to wait for social coupon deals with high discounts and check deal availability daily. Thus, promoting coupons among this cohort is likely to attract more participation and benefit businesses through increased profit and customer base expansion.

Deal proneness is a potential factor influencing social coupon redemption. Marketers should focus on targeting deal-prone customers by disseminating attractive deals to such customers. A database for deal-prone customers can be built by using past users' data and identifying individuals who arrived on the site through landing page links but did not avail of coupons. Marketing intelligence agencies can also provide a database of such deal-prone customers. Further, since deal pride exerts a positive influence on redemption, businesses should provide multiple benefits within the deals. This will make customers feel positive about the deal purchase and its redemption. It will make them feel smart and infuse a sense of achievement.

Furthermore, social influence and observation learning play a prominent role in driving social coupon redemption. Marketers must leverage these factors by employing influencer marketing techniques and leveraging social media platforms to promote such social coupon-based deals. Customers' eagerness toward the availability of deals, such as deal of the day, suggests that marketers should devise economically interesting deals. They should nudge customers toward such deals through social media alerts. Referrals also act as a factor influencing the social couponing phenomenon; thus, the promotion of sharable coupon deals is likely to benefit all the stakeholders. Prepayment for deals and membership programs provide customers with additional benefits. For example, these subscribers have a longer window of time to avail the discount. Organizations involved in designing promotional offers can benefit extensively by introducing membership offers and prepaid deals, which bring in advance payments from customers. Thus, group buying is associated with multiple additional benefits, making it popular among customers and businesses.

The outcomes of the structured equation modeling analysis contain useful insights for managers in the food sector. As prepayment/membership for deals and deals of the day exert a positive influence over coupon redemption, managers should focus on introducing such economical and unique offers that ensure both customers' interest and participation. Moreover, the emotional aspect pertaining to deal availability and deal purchase can be leveraged by managers through the introduction of newer deals over the holidays and the festive season. Further, the fact that consumption frequency does not play a significant role in coupon redemption is a signal that practitioners should focus on the quality of the products rather than the quantity. Finally, since a higher share of younger individuals participate in the redemption of social coupons, businesses should come up with innovative marketing strategies to attract such customers, including segment-specific products and deals.

8. Limitations and future research directions

There are certain limitations that should be taken into consideration by future scholars working in this domain. This study has exclusively focused on the food sector as the area of analysis. Future scholars should explore and analyze other sectors of the economy to understand the implications of social coupon promotions in those domains. Specifically, they should explore the impact of social coupons in e-commerce, personal care, and the cosmetic wellness industries, as these are high-growth customer segments. Metaverse is a new age growing social networking platform (Dwivedi et al., 2022). There is a need to explore the potential of social coupons for impacting product and service adoption and purchase on metaverse. A comparative analysis of the enablers of social coupon redemption between product and service industry organizations would also be for insights into these domains. By analyzing the behavioral aspects of individuals purchasing or using social coupons, marketers can better segment customers for targeting messages and offers.

It would be interesting for future scholars to explore how social coupons are different from traditional coupons in terms of their temporal and spatial characteristics. The role of social networking sites in accelerating the use of social coupons for product promotions should be further explored using large modern-retail datasets. Scholars can apply time-decay, single-touch, last-touch, linear, or other attribution models to e-commerce datasets to find optimal attribution models for different product and service categories. Demographic aspects like income levels of individuals, population density, marital status, and cultural aspects should be analyzed better to understand the best-case scenarios for implementing such coupons.

Scholars working in the domain should also explore the role of data analytics and blockchain in minimizing fraud in the social coupon redemption process. The impact of gamification in social coupon design should be analyzed from a redemption perspective. The commercial impact of integrating social coupons into existing loyalty platforms, including on social commerce sites, should also be explored. Ethical dimensions like capturing extra information while selling or redeeming social coupons, delayed service to coupon-availing customers, and using social coupons to cross-sell expensive items, as well as their impact on customer satisfaction and re-purchase intention, should be further explored.

9. Conclusions

Results from SEM analysis show that perceived risk and consumption frequency, as moderators, have no significant influence over the social coupon redemption decisions of the customers. Likewise, referrals and social influence have no significant influence over social coupon redemption. However, group buying, observational learning, prepayment, and deal of the day exert a positive influence over coupon redemption. With regard to deal activators, deal proneness and deal eagerness positively influence coupon redemption, but deal pride does not. Hypotheses H3, H4, H5, H6, H7, and H9 are accepted, whereas H1, H2, H8, H10 and H11 are rejected. These results suggest that customers involved in the process of social coupon redemption have a positive approach toward the factors that impact it. Further, it can be deduced that these factors have a positive influence on the purchase and redemption choices of customers in the context of the food industry. ML models have been employed in this study to understand and analyze the influence factors affecting coupon redemption behavior in the food industry, and the decision-tree algorithm provides valuable insights. Significant mediation and moderation effects have been recorded. Online delivery of social coupons has enabled product sellers and coupon aggregators to track consumer data on a real-time basis. Further, ML-based techniques can predict coupon redemption patterns such that they are more accurate and closer to actual social coupon redemption.

Our analysis shows that consumption frequency is the most important variable moderating individual redemption choice behavior. Perceived risk also has a significant impact on people's redemption choices. In other words, individuals experience a certain amount of risk when they have to share information while redeeming social coupons. However, as the frequency of use of social coupons increases, their risk perception decreases. This is due to better awareness of the platform, technology, and various information interfaces. Overall, it is evident from the analysis that social coupons, as a promotional feature, strongly influence customers' purchase preferences in the food industry context.

The concept of social couponing encompasses social aspects of customers participating in the redemption process. An increase in group purchases and referrals also augurs well for the growth of social coupons among customers. Technological advancements have also supported the social couponing phenomenon, allowing customers across the globe to share information about deals and engage in group buying. Modern technology has facilitated increased levels of engagement, including on social gaming and metaverse platforms, delivering higher profits to the businesses and deeper discounts and benefits to the customers. Further, social couponing facilitates social change among customers and businesses by bringing together customers to refer and buy products and services.

CRediT authorship contribution statement

Pappu Kalyan Ram: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Neeraj Pandey:** Conceptualization, Investigation, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Jinil Persis:** Conceptualization, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techfore.2023.123093.

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Pappu Kalyan Ram is a doctoral student in Marketing area at IIM Mumbai. He holds a post graduate degree in Computer Science and Systems Engineering. He has two years of industrial experience with Capgemini. His research interests are digital marketing, integrated marketing communication, and services marketing.

Neeraj Pandey is a Professor in Marketing Area at IIM Mumbai. His research has appeared in journals like *Australasian Marketing Journal*, *International Journal of Information Management*, *International Marketing Review*, *Journal of Business Research*, *International Journal of Contemporary Hospitality Management*, *Journal of Business and Industrial Marketing*, *Journal of Consumer Marketing*, *Journal of Strategic Marketing*, *Australasian Journal of Information Systems*, *Marketing Intelligence and Planning*, *Psychology & Marketing*, *Journal of Computer Information Systems*, and *Journal of Consumer Affairs*, among others. His research interests include pricing, digital marketing, B2B marketing, and product management.

Jinil Persis is Assistant Professor in Quantitative Methods and Operations Management Area at IIM Kozhikode. She has published in reputed journals like *Annals of Operations Research*, *Production Planning & Control*, *Journal of Environmental Management*, *IEEE Transactions on Engineering Management*, *Journal of Cleaner Production*, among others. Her research interests are operations management, evolutionary computation, and machine learning applications.